Upside-Down Down-Under: Cold Temperatures Reduce Learning in Australia

Upside-Down Down-Under:
Cold Temperatures Reduce Learning in Australia

David W. Johnston*, Rachel Knott*, Silvia Mendolia** & Peter Siminski***

August 2021

Forthcoming in *Economics of Education Review*

Abstract

Understanding how variation in weather and climate conditions impact productivity, performance and learning is of crucial economic importance. Recently, studies have established that high temperatures negatively impact cognition and educational outcomes in several countries around the world. We add to this literature by analysing test scores from a national assessment of Australian children aged between 8 and 15 years. Using comparable methods to previous studies, we find that high temperatures in the year prior to the test do not worsen performance. In fact, we find the opposite: additional cold days significantly reduce test scores. Moreover, the effect appears cumulative, with cold school days 1-2 years prior also having a negative effect. This seemingly contradictory finding is consistent with a literature which finds that people living in warm regions tend to inadequately protect themselves from cold temperatures, meaning they are susceptible to cold weather shocks. These results are also consistent with concerns about potentially harmful effects of unflued gas heaters in schools. More generally, we demonstrate that effects of weather conditions are context specific.

Keywords: Learning, Test scores, Weather, Climate, Australia

JEL Codes: I20, J24, J54

---

* Centre for Health Economics, Monash University ** School of Business, University of Wollongong *** Economics Discipline Group, University of Technology Sydney. Corresponding Author Details: Peter.Siminski@uts.edu.au; Department of Economics, University of Technology Sydney, 15 Broadway, Ultimo NSW 2007, Australia. We acknowledge funding from the Australian Research Council, grant number: DP170100177. This project was approved by the UOW & ISLHD Social Sciences Human Research Ethics Committee (Ethics No. 2017/259) and the NSW State Education Research Applications Process (SERAP No. 2017304). The findings and views in this paper are those of the authors and should not be attributed to the NSW Department of Education.

1. Introduction

Increased average temperatures and extreme weather due to climate change has focussed attention on how environmental factors impact human capital accumulation and performance in cognitively demanding tasks. The preponderance of evidence from economics suggests that high temperatures (hot days) have a negative effect on a range of cognitive outcomes. Cho (2017), Graff Zivin et al. (2018), Roach and Whitney (2019), Park (2020), Park et al. (2020a, 2020b), and Graff Zivin et al. (2020) all demonstrate that high temperatures on the test day and/or in previous days reduce student test scores.[1] Similarly, high temperatures have been found to reduce trade performance by stock market investors (Huang et al. 2020), affect decisions by US immigration judges (Heyes and Saberian, 2019), and weaken performance in cognitively intensive sport (Qui and Zhao, 2019).

But are the strong negative temperature effects universal? Older literatures studying the relationship between temperature and health find substantial heterogeneity across geographical regions, demonstrating that environmental context is crucial. For example, Curriero et al. (2002) conclude that "populations in warmer regions tend to be most vulnerable to cold, and those residing in cold climates are most sensitive to heat" (p.85). Vardoulakis et al. (2013) compared temperature-related mortality patterns in the UK and Australia, countries with similar socioeconomic characteristics but very different climates, and support this conclusion: heat-related mortality risks in Sydney were lower than in London, while the reverse was true for cold-related mortality.

A likely explanation for this counter-intuitive pattern is that people living in warm climates inadequately protect themselves from cold temperatures. Buildings in warmer climates tend to have inferior thermal efficiency (e.g. insulation) than buildings in cooler climates (Healy, 2003; Moore et al., 2019).[2] Similarly, residents of warmer climates are less likely to wear appropriate

[1] Cook and Heyes (2020) explore the cognitive effects of very cold temperatures (e.g. <15°C) relative to cold temperatures (2.5°C). They find that university exam performance in Ottawa worsens as the outdoor temperature declines. Mean temperature in the sample is around -5°C.

[2] Friedman (1987) argued it is rational for houses in warm climates to be colder than houses in cold climates. The article begins with the statement "A native of Chicago who spends a winter in Los Angeles or Canberra [Australia] is likely to find the houses uncomfortably cold and to express surprise that the natives are too stingy to heat their houses properly even though it would cost very little to do so" (p.1089).

clothing in winter.[3] The large empirical Eurowinter study (1997) concludes that "protective measures against a given degree of cold were fewer in regions with mild winters", implying that residents of warmer climates are particularly susceptible to cold weather shocks.

Given this context, it is important to explore whether the negative temperature-cognition relationship can be replicated in different environments around the world. This is the aim of our study. We estimate the effects of temperature on maths and literacy test scores in Australia using individual-level data on over 2.2 million national standardised tests taken by almost 400,000 students in over 1,500 schools between 2009 and 2018 in New South Wales.[4] The tests are taken each year in May by nearly all students in grade 3 (age 8-9), grade 5 (age 10-11), grade 7 (age 12-13) and grade 9 (age 14-15). The wide range of ages allows us to explore the effects of temperature at younger ages than most previous studies. With matched government administrative data, we can also explore the moderating effects of family and school socioeconomic status.

Comparing the within school-grade performance of students exposed to different temperatures across time, and controlling for test-day and non-school-day temperatures, we do not find a negative effect of heat on test scores. In fact, we find the opposite relationship: cold days significantly reduce test performance. Importantly, the effect sizes are large. Experiencing 10 additional school days with a maximum temperature <60°F (<15.6°C) in the year prior to the test, instead of ten warm school days, is estimated to decrease test scores by 1.2% of a standard deviation. Moreover, the negative effects appear cumulative, with cold school days 1-2 years prior to the test also having a negative effect on scores.

These findings for Australia suggest that the negative temperature-cognition relationship does not hold worldwide. Students (and others) may be more vulnerable to whatever weather conditions they are less accustomed to, or prepared for.[5] These results are also consistent with concern about potentially harmful effects of unflued gas heaters, which continue to be used in NSW public schools.

[3] The Eurowinter study (1997) found that at the same cold-weather temperature (7°C), residents of Finland were much more likely to wear a hat than residents of Greece (72 percent versus 13 percent). Hats are important because the head has low internal insulation in the cold.
[4] New South Wales is Australia's most populated state at approximately 8 million people. The state's capital city is Sydney.
[5] Our findings do not imply that climate change will improve student performance in NSW. Climate change is increasing average temperature as well as weather variability.

The remainder of the paper is structured as follows. Section 2 describes data and methods. Section 3 presents the results and robustness tests. Section 4 discusses potential mechanisms and Section 5 concludes.

2. Data and Methods

2.1. Data and Descriptive Statistics

We use individual-level test score data from the National Assessment Program—Literacy and Numeracy (NAPLAN) for all New South Wales (NSW) Government (i.e. public) schools. NAPLAN is an annual assessment of students in grades 3, 5, 7 and 9, designed to measure grade-specific knowledge. The tests cover knowledge in the areas of reading, writing, language conventions (spelling; grammar and punctuation) and numeracy. They are undertaken every year in the second week of May, and all students across Australia sit the tests on the same days.

Students with significant intellectual disability and students who arrived in Australia less than one year before the tests may be exempted from testing (Miller and Voon, 2012). Parents also have the possibility to withdraw their children from the tests, for reasons such as religious beliefs and philosophical objections to testing. Overall, NAPLAN participation rates are over 90% in all subjects and grades (ACARA, 2019, AIHW, 2018).

Our anonymised data were provided for all students who attended a NSW Government school between 2009 and 2018, and who completed at least three assessments during these years. After dropping unusual year-grade cells, our main estimation sample includes: grade 3 test score observations from 2009 to 2014; grade 5 observations from 2010 to 2015; grade 7 observations from 2012 to 2018; and grade 9 observations from 2014 to 2018.[6]

In addition to test results, the data contain date of birth and gender of each student, quartile of socio-educational advantage (derived from parental occupation and education) and the school in which they were enrolled when they completed the test. School-level data is also provided

[6] The different sample years by grade are due to the data requirement that students completed at least three assessments. For example, most students who completed their grade 3 NAPLAN test in 2015, completed their grade 5 NAPLAN test in 2017, and their grade 7 NAPLAN test in 2019. However, 2019 is outside our sample range, and therefore these students do not have three observed assessments, and so do not appear in our data set.

including geographic coordinates and index of community socio-educational advantage, which represents relative socioeconomic status of students in a particular school (ACARA, 2015).

Data from the Australian Bureau of Meteorology were used to construct various temperature variables. Specifically, we matched each school to its five closest weather stations, and calculated the weighted average daily maximum temperature, with weights equalling the inverse squared Euclidian distance from schools to stations. Some schools are far from weather stations, introducing measurement error in the predicted temperatures for those schools. To reduce the associated attenuation bias, we restrict our main analysis to all students attending schools within 20km of at least one weather station (90 percent of all students). With this restriction, mean distance to the closest weather station is 7.48km. In a robustness analysis reported below, we test the sensitivity of our results by relaxing the 20km distance restriction.

Table 1 shows descriptive statistics for the main variables, for the main estimation sample. Figure 1 shows the distribution of temperatures across school-years included in the main estimation sample. Panel A shows the distribution of mean maximum temperatures. For 90% of student observations, the mean temperature is between 70°F and 78°F. Panel B shows the distribution of the number of cool school days (maximum < 70°F). This distribution is wide, ranging from 15 to 186.

Figure 2 shows the geographic distribution of temperatures across NSW, by Local Government Area. Panel A is coloured according to mean maximum temperature, while Panel B is by number of cool school days. The inserts show the Sydney region, where over 60% of the NSW population live. The regions with the coldest temperatures are towards the south, and near the Great Dividing Range, a mountain range which spans the length of the state (and beyond), roughly parallel to the east coast.

2.2 Methods

To estimate the effects of hot and cold days on student performance, we exploit year-to-year variation in temperature within a grade in a given school. Specifically, we estimate a baseline specification of the form:

$$y_{igst} = \sum_{j=1}^{J} \beta_j Temp_{j,st} + \alpha_{sg} + \theta_{gt} + \lambda T_{st} + \gamma X_{it} + \varepsilon_{igst} \qquad (1)$$

where y_{igst} is the standardized numeracy or literacy score (multiplied by 100) for student i in grade g at school s in year t.[7] $Temp_{j,st}$ is the number of school days in the prior twelve months in which the maximum temperature was in bin j. Potentially confounding factors, such as school infrastructure and student socioeconomic status, are controlled for with the inclusion of school-grade fixed effects (α_{sg}). Changes over time in the test itself are controlled for with year-grade fixed effects (θ_{gt}). Regression (1) also includes controls for temperatures on non-school days and test days (T_{st}), and controls for student characteristics (X_{it}).

Under the plausible assumption that temperature varies randomly across years within a given school, estimates of β_j can be interpreted as the causal effect of exposure to hot and cold days on student performance. We test the validity of this assumption by conducting a placebo test in which we regress future temperatures on tests scores. We also regress student-level characteristics, such as family socioeconomic status, on temperature to determine whether there is an association between changes in student 'quality' and changes in temperature, within schools over time. The results are discussed in detail in Section 3.3; but the key take-away is that the identification assumption appears valid.

We explore the sensitivity of β_j by presenting estimates from regressions that include control variables representing: (i) other weather conditions; (ii) atmospheric pollution; (iii) local economic conditions; and (iv) area-specific linear time trends (see Section 3.2). We also present estimates from a regression that includes student fixed-effects in addition to the school-grade fixed effects and year-grade fixed effects (see Section 3.3). The estimates from these alternative specifications support our main conclusion.

Finally, we estimate versions of regression (1) in which $Temp_{j,st}$ is replaced with (i) mean maximum school-day temperature over the previous 12 months, (ii) indicators of the decile of mean maximum school day temperatures, (iii) number of school days with mean temperature in bin j; and (iv) number of school days with minimum temperature in bin j.

[7] We standardize test scores by subject (literacy and numeracy), grade level and calendar year.

3. Results

3.1. Baseline Estimates

The main results are shown in Figure 3. Panel A shows estimated effects of cold and warm school days, relative to 70-75 degree days. The results suggest that one additional cold school day (<60°F) reduces test scores by 0.15 hundredths of a standard deviation (HSD), one additional 60-65°F day reduces scores by 0.10 HSDs, and one additional 65-70°F day reduces scores by 0.09 HSDs. These magnitudes are comparable to, indeed larger than, Park et al.'s (2020) estimated effects of hot days.[8]

Appendix Figure A.1 shows estimates from similar models which instead use minimum and mean (average of max and min) daily temperatures. The results support the main finding that relatively cold days are associated with lower test scores. The results are strongest for maximum temperatures, and weakest for minimum temperatures, suggesting that school-time temperature is more important than night-time temperature.

Panel B of Figure 3 shows estimated effects of the average maximum temperature of all school days in the past year. Estimates for each decile are relative to years in the 5th decile. Visually, there is a similar pattern as in Panel A, with the graph suggesting that lower test scores coincide with cooler temperatures. The test scores following years in the 1st, 2nd and 3rd deciles of the temperature distribution are estimated to be 1.94, 3.63 and 1.82 HSDs lower than test scores following a year in the 5th decile.[9] In contrast, the estimated effects for the upper deciles are all close to zero.

Importantly, these estimated relationships are clearly different to those presented in previous research, such as in Park et al. (2020). There is no evidence that hot days or hot years have any impact relative to moderate days or years. In Panel A the estimated coefficients of the highest four temperature categories are all small, similar and statistically insignificant. The results are similar for relatively high deciles in Panel B. However, the 95% confidence intervals are large for the estimated effects of hot days, and we cannot rule out reasonably large effects.

[8] However, these differences in magnitudes are not generally statistically significant, reflecting the relatively large standard errors in our estimates. One useful comparison is between overall estimates of cool and hot days. Our estimate for cool days is -0.083 (Table 3, Column 1), whilst Park et al.'s (2020: Table 3) comparable estimate for hot days is -0.056. The difference between these two estimates is not statistically significant ($p = 0.26$).
[9] The average temperatures in the 1st, 2nd, 3rd, and 5th deciles equal 67.8°F; 71.3°F; 72.1°F and 73.4°F.

Table 2 shows corresponding regression estimates. Column (1), Panel A shows estimates based on the main specification, but with a continuous variable representing average annual school day temperature (instead of temperature deciles as in Figure 3B), while Column (1), Panel B shows the results which correspond to Figure 3A. The estimate in Panel A is positive (0.436), but is not statistically significant. Therefore, we conclude that there is no strong evidence of a linear relationship between temperature and test performance.[10]

3.2. Estimates from Expanded Specifications

Columns (2) to (6) in Table 2 test the sensitivity of the baseline results to the inclusion of additional control variables. Column (2) includes controls for rainfall, wind and humidity on school days in the past year and on the test day, and Column (3) controls for school day and test day atmospheric pollution.[11] These variables are added because they are correlated with temperature, and may also affect student outcomes. In both columns, the coefficient estimates for number of school days in the past year that were <60°F, 60-65°F and 65-70°F are only slightly smaller than the corresponding estimates in Column (1).

Column (4) controls for the local unemployment rate in the past year, because temperature-driven shocks to the local economy might affect child wellbeing. For example, through parental mental health. Again, the estimates are similar to those in Column (1). Column (5) includes indicators of family socioeconomic status quartile, which are based on an index of parental education and occupation.[12] The estimates from this specification have the same pattern as previous regressions – cold days are associated with lower test scores – but the coefficient estimates for number of school days < 60°F is somewhat reduced from -0.148 to -0.118.

---

[10] To account for possible nonlinear annual temperature effects (Burke *et al.*, 2015), we re-estimated this model with the inclusion of a quadratic function of temperature. The estimated coefficient of temperature-squared was close to zero (0.003) with p-value equal to 0.89. The p-value for the joint significance test of the linear and squared coefficient terms is 0.30.

[11] The pollution controls are constructed from the Air Quality Index. This is based on atmospheric concentrations of ozone, nitrogen dioxide, carbon monoxide, sulphur dioxide, particular matter (PM)-2.5 and PM-10, and visibility, collected from monitoring stations around the state. See https://www.environment.nsw.gov.au/topics/air/understanding-air-quality-data/air-quality-index

[12] This variable was provided by the data custodian, who advised that "Socio-educational advantage (SEA) quarter classifies students into one of four quarters on a measure derived from parental occupation and education attributes. Parental occupation and education data is complete for over 90% of students. However, for students with incomplete parental data, a multiple imputation methodology is used to impute missing values based on other available student level data plus area-based community variables from the ABS census associated with the statistical area level 1 (SA1) of student addresses." The sample size in Columns (5) and (6) of Table 2 is smaller than in other columns, because of missing information on the socioeconomic status of around 4% of students.

Finally, in Column (6) we present estimates from a regression with all of the weather, pollution, and economic controls included simultaneously.[13] This specification indicates that one additional school day in the past year that was <60°F is estimated to reduce test scores by 0.12 hundredths of a standard deviation (HSD), and one additional 60-65°F school day is estimated to reduce test scores by 0.08 HSDs. The estimated effect for school days 65-70°F in Column (6) is considerably smaller than in the baseline specification and is also more precisely estimated. We therefore place less emphasis on the test score effect of temperatures within this particular range.

Another interesting result from Column (6) is the relatively large positive coefficient estimate associated with number of school days >90°F (= 0.089). The pattern of negative coefficient estimates for cold days, and nearly as large positive coefficient estimates for hot days, is reflected in the now large and statistically significant coefficient on average temperature. The estimate of 0.863 indicates that a one degree increase in the average school day temperature in the past year is estimated to increase test scores by 0.86 HSDs.

3.3. Placebo and Robustness Tests

As a simple placebo test, we re-estimate our main specification, using weather data from the 12 months after the test, rather than from the 12 months prior. If changes in temperature are spuriously associated with changes in student or school quality, then we may find a pattern similar to that shown in Figure 3A. The results shown in Appendix Figure A.2 support our empirical approach. None of the estimates are statistically significant, nor do they follow any systematic pattern.

Next, we test whether temperature influences student composition within schools. In Appendix Table A.2, we show results from regressions with student characteristics as the dependent variables, instead of test scores (control variables are as in Column 1 of Table 2). Column (1) presents results for family socioeconomic status as the dependent variable, expressed in quartiles: = 1 for the bottom quartile (disadvantaged) and = 4 for the top quartile (advantaged). Only one coefficient is statistically significant, and there is no systematic pattern in the

[13] Appendix Table A.1 shows the full set of coefficient estimates from the model with all controls.

estimates. Estimates in Columns (2) and (3) are similar to those in Column (1), demonstrating no association between temperature and the composition of schools in terms of gender or age.[14]

Another potential concern is that there is an association between temperature and unobserved factors in the school's local area, which in-turn affect student scholastic performance. To explore this possibility, we estimate regressions that additionally include area-specific linear time trends. Specifically, we include a separate trend term for 128 Local Government Areas within NSW. The estimates are very similar to those in Column (6) of Table 2: an additional school day <60°F and 60-65°F is estimated to reduce test scores by 0.115 HSDs and 0.086 HSDs, respectively.

Our fourth test involves controlling completely for time-invariant student characteristics through the inclusion of student-fixed effects. Specifically, we estimate a regression with student fixed-effects, school-grade fixed-effects and year-grade fixed-effects. The estimates indicate that additional cold days significantly reduce test scores. The estimated coefficients on the number of days <60°F and number of days 60-65°F are statistically significant and equal -0.069 and -0.070, respectively. The estimate for number of days 65-70°F equals -0.026 and is statistically insignificant from zero. Overall, these estimates support our previous findings regarding cold weather, but are distinctly smaller than those shown in Table 2. An explanation for this difference is that the additional third level of fixed-effects means that identification of the temperature coefficients become reliant on test score changes among a much smaller proportion of observations. This smaller sub-set of observations are likely to be different than the sub-set of observations driving the identification in our main specification.

A different potential source of estimation bias comes from measurement error in our temperature variables caused by schools being located far from weather stations. The main analysis excludes schools farther than 20km from a weather station, but we have tested the sensitivity to alternative distance restrictions. The results demonstrate that increasing the allowable distance introduces attenuation bias. For example, estimated effects for school days <60°F are 31% larger for our main sample (within 20km) than for the sample using all schools within 50km of a weather station. However, regardless of the restriction, we find that more cold school days is associated with lower test scores.

[14] The age composition of schools can increase if a greater proportion of parents delay enrolling their age-eligible child in school (known sometimes as redshirting). In Australia this practice is common, especially in higher socioeconomic status areas.

Our next robustness check involves exploring how the estimates change with different estimation samples. The original data provided by the custodian were restricted to students who completed at least three (NAPLAN or HSC) assessments between 2010 and 2018. This leads to some unusual sample characteristics. For example, Year 7 results for 2010 and 2011 were only provided for the subset of students who completed the Year 12 exam (HSC), but for later years, students did not need to complete the HSC to meet the selection criteria. In the main analysis, we exclude observations in such clearly anomalous cells. Estimates from regressions that do not exclude these observations are very similar to those in Table 2: estimate for school days <60°F equals -0.146, compared with -0.148. Estimates are also similar when using a smaller sample that ensures that student-year observations are included strictly consistently across calendar years for each grade.[15]

In our final robustness test we consider sensitivity of the key results to inclusion of other temperature controls (weekends and holidays). If we exclude weekend temperature covariates from our baseline specification, the estimated effects of school day temperatures are slightly smaller than in Table 2. Estimated coefficients on the number of days <60°F and number of days 60-65°F equal -0.130 and -0.086, respectively. If holiday temperature covariates are included, the estimates are again similar to the baseline specification. Estimated coefficients on the number of days <60°F and number of days 60-65°F equal -0.126 and -0.073, respectively.

3.4 Lagged and Cumulative Effects

We now consider whether the effects are temporary or have lasting effects on student performance. Table 3 shows results from regressions based on the baseline specification, with two modifications. For parsimony, these regressions include just one variable measuring the number of cool days (<70°F). This value is chosen, even though the upper limit of 70°F is not particularly cold, because all the estimates in Table 2, suggest that the cool weather effects begin in the 65-70°F range. The other modification is that some regressions also include variables representing lagged number of cool days.

[15] There is more than one way to construct such a sample. We show results from the version that yields the largest sample size. Further details available from the authors.

Column (2) includes one lag, which captures the effect of cool school days between 24 and 12 months prior to the test date. Column (3) includes two lags. Each column also includes an estimated 'cumulative' effect, which is the sum of the lagged and unlagged coefficients. These results are consistent with Park et al. (2020) in the sense that the effects are not completely transitory. A temperature shock in the past year that increases the number of cool school days is estimated to effect test scores this year (-0.100) and next year (-0.089). The cumulative three-year effect (-0.211) is estimated to be 2.5 times greater than the one-year effect.

3.5 Heterogeneity

Whilst constrained by statistical power, we now consider heterogeneity in the estimated effects of temperature on test scores. Each estimate in Figure 4 is from a regression based on the baseline specification, with the variable of interest defined as days where the maximum temperature was <70°F, estimated using only the subpopulation of interest. The first estimate at the top of Figure 4 is for students at schools where cool days are relatively rare. These are schools in the bottom half of the distribution of the average annual number of school days <70°F. The next estimate is for schools in the top half of the distribution. The difference between these two estimates is not statistically significant. However, the point estimate is close to zero for schools where cool days are not rare. This provides support for our conjecture that cool days may be more harmful in areas accustomed to warm or hot weather.

The next pair of estimates are for schools where air-conditioning coverage in teaching spaces is low vs high. The air conditioning data are for a single point in time, collected in a survey undertaken between November 2016 and December 2017. Average air conditioning coverage in teaching spaces is 25% for schools in the 'low' air conditioning group, and 95% in schools in the 'high' air-conditioning group. The effects of cool days are clearly concentrated in schools with low air-conditioning coverage. This result is explained by the fact that air-conditioners are likely to be used for heating as well as cooling. This explanation is further discussed in Section 4.

Regressions estimated separately for primary school students and high school students show that the estimated point estimate is much higher for high school students. A possible explanation for this result is that air-conditioning coverage is much higher in primary schools than secondary schools: 75% vs 41% of teaching spaces, in our data. More broadly, younger children are likely more closely monitored and guided on their clothing and environment, with older children more likely to make their own choices and hence more vulnerable to weather fluctuations. We are not aware of previous related studies which have examined heterogeneity by age of children.

The estimated effects are larger for boys than for girls. This is consistent with previous studies. In particular, Cook & Heyes (2020) find larger effects of cold weather on test scores for boys, also citing earlier work which suggests female students wear more layers of clothing in cold weather (Donaldson et al., 2001). Cho (2017) also finds slightly larger effects of heat on test performance for boys. Ebenstein et al. (2016) found male test performance to be more vulnerable to pollution, while a broader literature finds male mortality more vulnerable to heat (e.g. Deschênes & Greenstone, 2011).

Park et al. (2020b) found much larger immediate effects of heat for low income and minority students, partly due to differential access to air-conditioning in schools and homes. We do not find such heterogeneity. This may reflect NSW's centrally funded public school system, in which SES-related discrepancies in air-conditioning, insulation and heating are less likely. We also find only a small difference between estimates for English and Math test scores. The slightly larger English effect consistent with Cho (2017), although Cho also found no significant effect for reading. Others have found similar effects of temperature across English and Maths tests (Park et al. 2020b; Roach & Whitney, 2019).

4. Exploring Mechanisms

A likely explanation for our results is that Australian people are accustomed to warm and hot temperatures, and lack awareness on appropriate preparation for cold weather (Barnett et al., 2017; Howden-Chapman et al., 2017). Australian houses and buildings are generally unprepared for moderate amounts of cold weather, mostly because of inadequate heating systems and poor insulation (Daniel et al., 2019; Moore et al., 2019, among others). Schools and classrooms are subject to similar problems, including having inadequate heating, and buildings that unable to maintain warmth in moderately cold weather.

In this section, we discuss two specific mechanisms, which are related to this explanation: (i) increased sickness absenteeism; and (ii) the use of unflued gas heaters in classrooms. We are able to test the first of these. We do not have data on unflued gas heaters, so we instead summarise the recent debates about using such heaters in the NSW schools.

4.1 Sickness and Attendance

A potential mechanism for the cold-day effect is through greater rates of student illness and/or school absenteeism. We explored this mechanism by estimating a school-grade and year-grade fixed-effects regression of student attendance rates. Our main student-level database does not include attendance records, and so we instead used publicly available school-year level data on average student attendance rates across the first half of each school year from 2011 to 2018.[16] The results shown in Figure 5 do not support a school absenteeism mechanism, with the U-shaped pattern of point estimates suggesting higher attendance is associated with more cold weather and more hot weather. The estimates are mostly statistically insignificant, and arguably small. For example, the point estimates suggest that a week of weather in the coldest category (relative to the omitted category) would increase attendance by less than 0.1 percentage points across the semester.

4.2 Unflued Gas Heating

Many schools in New South Wales still use unflued gas heaters. Such heaters present several health-related risks, because they produce toxic gases and must be used with appropriate ventilation in the classrooms (Marks et al., 2010). This usually means that at least one window in the classrooms needs to be open (NSW Government, 2018), which may drastically reduce heating efficiency (and increase heating costs).

Several studies in the Australian and international literature have showed that children exposed to high levels of nitrogen dioxide (produced by unflued heaters) had increased respiratory symptoms and more absent days from school (see Pilotto et al., 1997; Pilotto et al., 2004; Samet and Bell, 2004; Amnesi-Maesano et al., 2012; Cong et al., 2014, among many others). However, the evidence on long term health consequences is not conclusive (see Amnesi-Maesano et al., 2013 for a review of the evidence).

[16] For this analysis we use weather data from the first half each school year, to match the attendance data.

After calls from parents' and teachers' associations for a commitment from the Department of Education and Training to remove all unflued heaters (see for example Barnes, 2009; Lemaire, 2010; Lemaire, 2011), the process of removing these heaters from NSW classrooms started in 2010. This process is still in progress (part of the so-called "Cooler Classroom Program"), but is far from complete. It is also focussed on installing air-conditioning in hot areas, not on replacing heaters where they are most heavily used (NSW Department of Education, 2018; Harris, 2020; Baker, 2021).

As discussed in Section 3.4, the effects of temperature on test scores are apparent only in schools with low air-conditioning coverage. Since air-conditioners are likely to be used for heating, our results are consistent with unflued gas heaters as a potential mechanism.

5. Conclusion

Unlike several previous studies for other countries, we have found that cold, not heat, inhibits learning in Australia. The estimated effects are meaningful. For example, experiencing 10 additional school days with a maximum temperature <60°F (<15.6°C) is estimated to decrease test scores in the same year by 1.2% of a standard deviation. Moreover, the effect sizes are larger than the heat effects presented in most previous studies.

The heterogeneity analysis is statistically under-powered, but suggests that these effects are concentrated in schools where cool days are relatively rare, in schools with low air conditioning coverage, and (perhaps consequently) in secondary schools rather than primary schools. These results are also consistent with potentially harmful learning effects from the use of unflued gas heaters on cold days. We find little heterogeneity in effect size by family SES or by school SES.

The relationship we have identified here is in-line with studies on morbidity and mortality that demonstrate cold temperatures are particularly damaging in hot regions with mild winters, and conversely, that hot temperatures are particularly damaging in cold regions with mild summers. International research suggests that this difference is due to populations in hot regions inadequately protecting themselves from cold temperatures. Australia has an ingrained identity of a sunburnt country, and has a long history of focusing on adaption and resilience to hot temperatures, rather than cold (Daniel et al., 2019). Further research is needed to determine whether the positive test-score temperature gradients that have been robustly identified in the U.S., China, Korea and other countries, have broad external validity, especially in regions with mild winters and hot summers.

References

ACARA. (2015). What does the ICSEA value mean?. Australian Curriculum, Assessment and Reporting Authority. Available: https://acara.edu.au [Accessed May 2020].

ACARA (2019). NAPLAN achievement in reading, Writing, language conventions and numeracy: National report for 2019. Sydney: Australian Curriculum Assessment Reporting Authority.

AIHW (2018). Australia's Children. Australia Institute of Health and Welfare. Available: https://www.aihw.gov.au [Accessed February 2021].

Baker, J. (2021). 'Gas cookers in homes have same impact on children as passive smoking: report' *Sydney Morning Herald*, 6th of May, 2021.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature, 527* (7577), 235-239.

Cho, H. (2017). The effects of summer heat on academic achievement: A cohort analysis. *Journal of Environmental Economics and Management*, *83*, 185-196.

Cook, N., & Heyes, A. (2020). Brain freeze: outdoor cold and indoor cognitive performance. *Journal of Environmental Economics and Management*, 102318.

Curriero, F. C., Heiner, K. S., Samet, J. M., Zeger, S. L., Strug, L., & Patz, J. A. (2002). Temperature and mortality in 11 cities of the eastern United States. *American journal of epidemiology*, *155*(1), 80-87.

Harris, C. (2020) 'School heaters still pose toxic risk', *Daily Telegraph*, 28th of July, 2020, Surry Hills.

Daniel, L., Baker, E., & Williamson, T. (2019). Cold housing in mild-climate countries: A study of indoor environmental quality and comfort preferences in homes, Adelaide, Australia. *Building and Environment*, 151, 207-218.

Deschênes,O. & Greenstone, M. (2011). Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, *3*(4),152–185.

Donaldson, G. C., Rintamäki, H., Näyhä, S. (2001). Outdoor clothing: Its relationship to geography, climate, behaviour and cold-related mortality in Europe. International Journal of Biometeorology, *45*(1), 45-51.

Eurowinter Group (1997). Cold exposure and winter mortality from ischaemic heart disease, cerebrovascular disease, respiratory disease, and all causes in warm and cold regions of Europe. *The Lancet*, 349, 1341-1346.

Friedman, D. (1987). Cold houses in warm climates and vice versa: A paradox of rational heating. *Journal of Political Economy*, *95*(5), 1089-1097.

Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., ... & Armstrong, B. (2015). Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *The Lancet*, 386(9991), 369-375.

Graff Zivin, J., Hsiang, S. M., & Neidell, M. (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists*, *5*(1), 77-105.

Graff Zivin, J., Song, Y., Tang, Q., & Zhang, P. (2020). Temperature and high-stakes cognitive performance: evidence from the national college entrance examination in China. *Journal of Environmental Economics and Management*, *104*, 102365.

Healy, J. D. (2003). Excess winter mortality in Europe: a cross country analysis identifying key risk factors. *Journal of Epidemiology & Community Health*, *57*(10), 784-789.

Heyes, A., & Saberian, S. (2019). Temperature and decisions: evidence from 207,000 court cases. *American Economic Journal: Applied Economics*, *11*(2), 238-65.

Huang, J., Xu, N., & Yu, H. (2020). Pollution and performance: Do investors make worse trades on hazy days?. *Management Science*, *66*(10), 4455-4476.

Miller, P. W. & Voon, D. (2012). Government Versus Non-Government Schools: A Nation-Wide Assessment Using Australian Naplan Data. *Australian Economic Papers*, 51, 147-166.

Moore, T., Berry, S., & Ambrose, M. (2019). Aiming for mediocrity: The case of Australian housing thermal performance. *Energy policy*, *132*, 602-610.

New South Wales Department of Education (2018) *Cooler Classrooms Program*, https://www.schoolinfrastructure.nsw.gov.au/news/2018/07/cooler-classrooms-program.html

Park, R. J. (2020). Hot Temperature and High Stakes Performance. *Journal of Human Resources*.

Park, R. J., Behrer, A. P., & Goodman, J. (2020a). Learning is inhibited by heat exposure, both internationally and within the United States. *Nature human behaviour*, 1-9.

Park, R. J., Goodman, J., Hurwitz, M., & Smith, J. (2020b). Heat and learning. *American Economic Journal: Economic Policy*, *12*(2), 306-39.

Qiu, Y., & Zhao, J. (2019). Too Hot to Focus: The Mean and Distributional Effects of Heat on Labor Productivity. *Available at SSRN 3421890*.

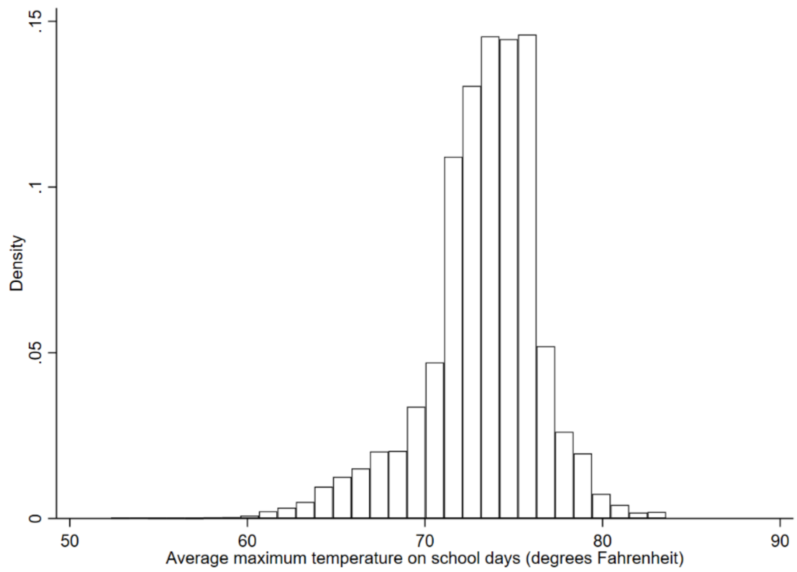
Roach, T., & Whitney, J. (2019). Heat and Learning in Primary and Secondary Education. *Department of Economics, University of Central Oklahoma*.

Vardoulakis, S., Dear, K., Hajat, S., Heaviside, C., Eggen, B., & McMichael, A. J. (2014). Comparative assessment of the effects of climate change on heat-and cold-related mortality in the United Kingdom and Australia. *Environmental health perspectives*, *122*(12), 1285-1292.

Figures

Figure 1 Distributions of School-Day Temperatures in the Previous Year

A: Average Maximum Temperature



B: Number of Cool School Days

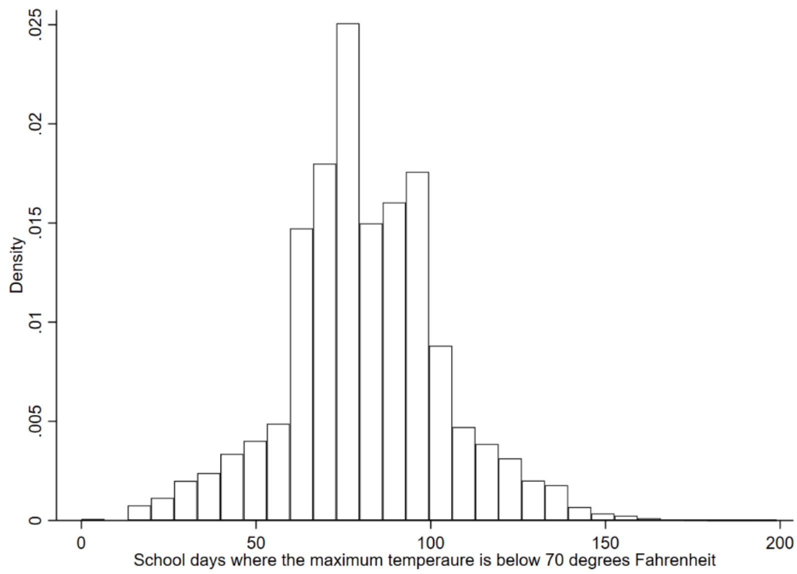
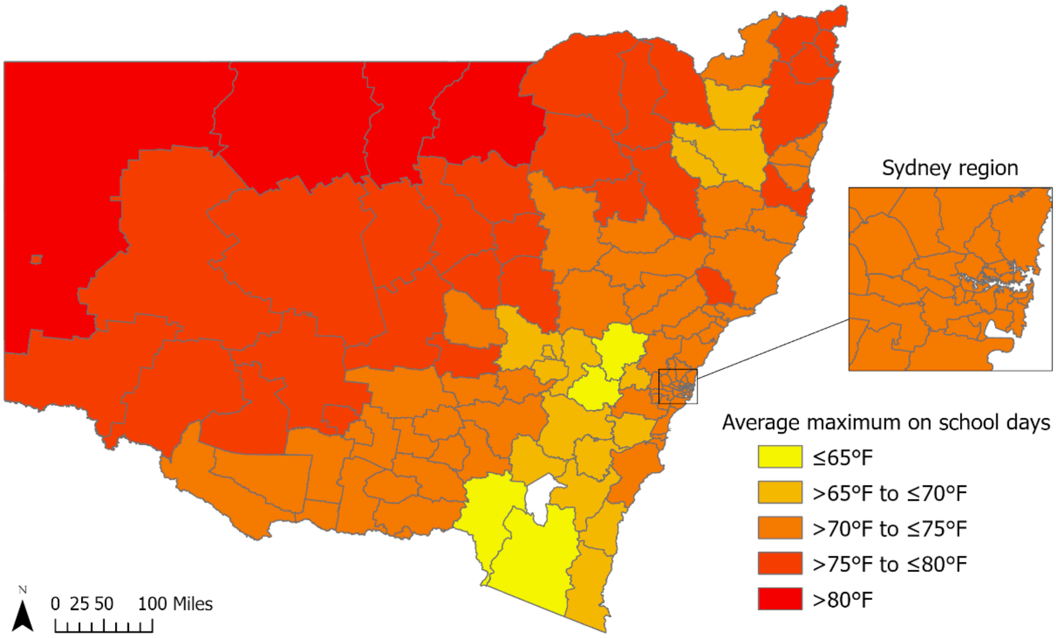


Figure 2 Temperature Statistics by NSW Local Government Areas

A: Average Maximum Temperature on School Days



B: Number of Cool School Days Per Year

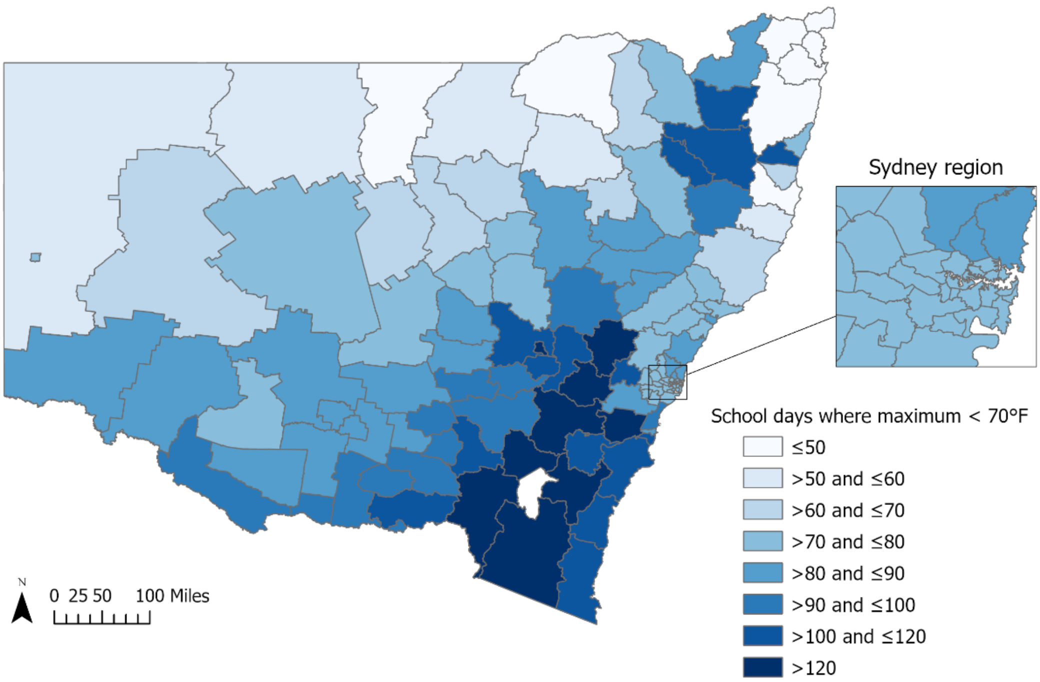
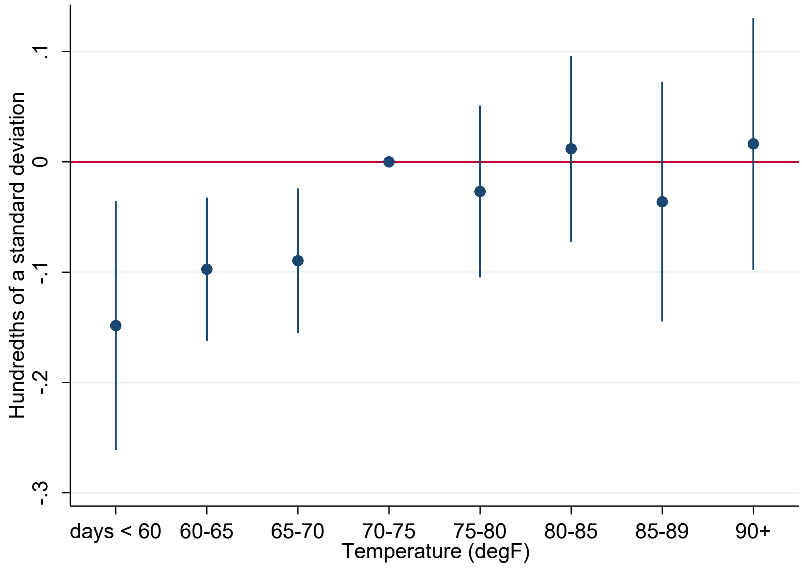
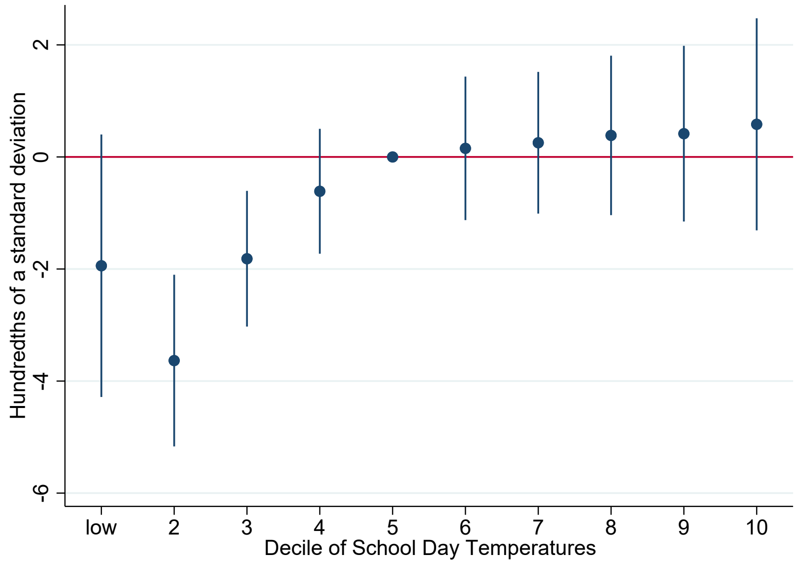


Figure 3 Test Score Effect Estimates from Baseline Regression Specification

A: Estimated test score effects of prior year school days with various maximum temperatures

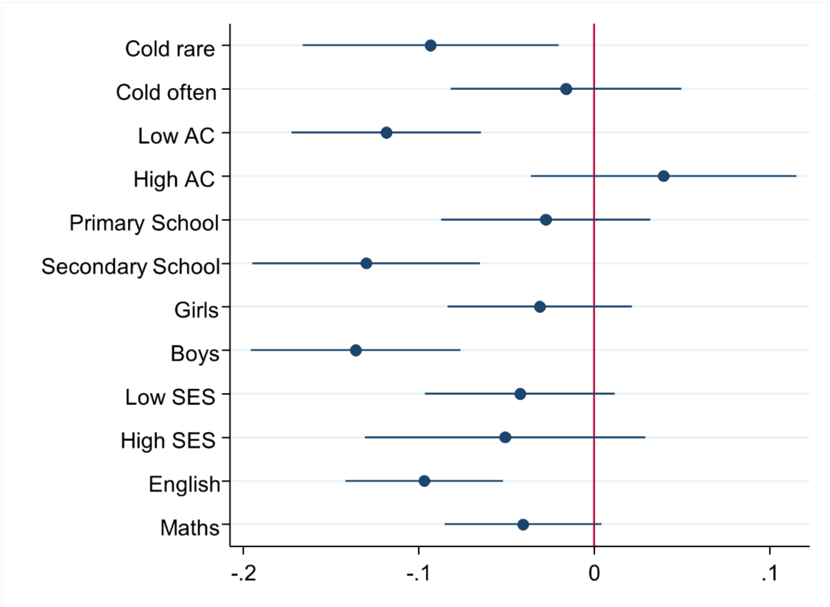


B Estimated test score effects of average prior year school day temperature by temperature decile



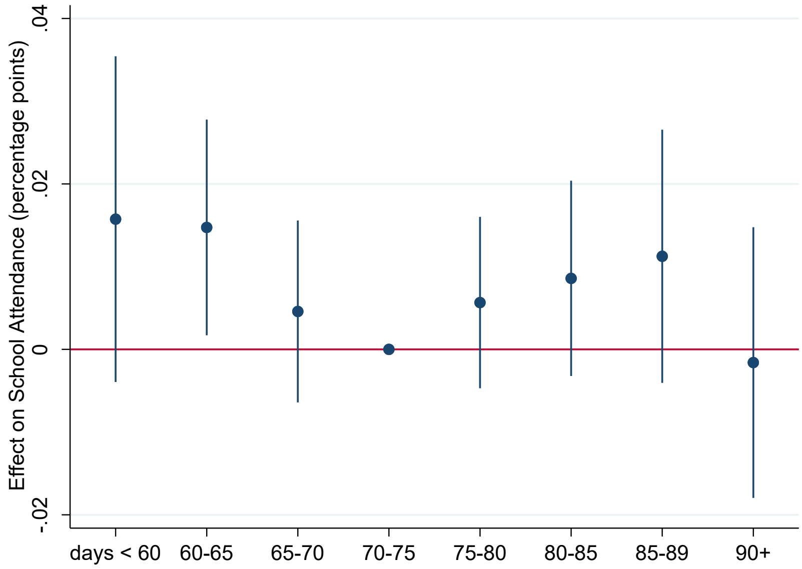
Note: Estimates from linear regression with the displayed temperature variables and the following covariates: number of weekend days in previous 12 months with maximum temperatures in the same ranges as shown for school days; max temperature on test day; age; gender; year-grade FE; and school-grade FE.

Figure 4 Estimated Effects of Number of Cool School Days, Separately by Student and School Factors



Note: "Cold rare" represents schools in the bottom half of the distribution of the average annual number of school days <70°F. "Cold often" represents schools in the top half of the distribution. "Low AC" represents schools with proportion of teaching spaces with air conditioning below the median and "High AC" represents schools with proportion of teaching spaces with air conditioning above the median.

Figure 5 Estimated school attendance effects of school days at various temperatures



Notes: This Figure shows the estimated effects of temperature on school attendance, drawing on school-year level data. The dependent variable is the average attendance rate across the first half of a school year for a given school. The key explanatory variables are the number of school days during the first half of the year in each temperature category. The empirical approach otherwise follows the main analysis.

Tables

Table 1 Descriptive Statistics

Variable	Mean	Std Dev
Standardized Test Score	0.02	1.01
Mean school day maximum temperature	73.47	2.51
Mean school day minimum temperature	54.04	3.39
Number of school days with max temp below 60°F	11.72	15.36
Number of school days with max temp between 60°F and 64°F	28.65	9.58
Number of school days with max temp between 65°F and 69°F	39.36	8.80
Distance (km) to nearest weather station	7.48	4.19
Age (years)	11.39	2.16
Female	0.488	0.500
Air conditioning coverage (0-1)	0.603	0.379
Primary school	0.568	0.495
Mean relative humidity on school days (%)	70.07	4.54
Average wind speed (km/h)	26.69	12.28
Prior year pollution (measured using the Air Quality Index)	45.79	7.53
Local unemployment rate (%)	5.58	1.52
Sample size	2,234,842	

Note: This table shows descriptive statistics for the main estimation sample. The mean and SD of the standardized test score are zero and one, respectively, amongst the broader sample before any restriction is applied on distance from school to nearest weather station. The Air Quality Index (AQI) is constructed using measurements of key air pollutants; specifically, particles less than 2.5 micrometres diameter (PM2.5), particles less than 10 micrometres diameter (PM10), ozone, nitrogen dioxide, sulphur dioxide and visibility. Our measurement of AQI comes from the NSW Department of Planning, Industry and Environment. The local unemployment rate is the average monthly regional unemployment rate over the 12 months prior to the NAPLAN test date.

Table 2 Estimated effects of temperature on NAPLAN test scores

	(1)	(2)	(3)	(4)	(5)	(6)
	A: Impact of average max temperature					
Average temperature	0.436	0.568	0.622**	0.450	0.523*	0.863**
	(0.278)	(0.380)	(0.286)	(0.280)	(0.271)	(0.379)
	B: Impact of number of school days in various max temperature ranges					
Days < 60°F	-0.148***	-0.147**	-0.144**	-0.158***	-0.118**	-0.116**
	(0.058)	(0.063)	(0.058)	(0.058)	(0.053)	(0.058)
Days 60°F to 65°F	-0.097***	-0.090**	-0.092***	-0.101***	-0.094***	-0.081**
	(0.033)	(0.036)	(0.033)	(0.033)	(0.032)	(0.035)
Days 65°F to 70°F	-0.090***	-0.076**	-0.085**	-0.088***	-0.075**	-0.055*
	(0.033)	(0.034)	(0.034)	(0.033)	(0.032)	(0.032)
Days 75°F to 80°F	-0.027	-0.028	-0.007	-0.026	-0.017	-0.002
	(0.040)	(0.040)	(0.041)	(0.040)	(0.039)	(0.039)
Days 80°F to 85°F	0.012	-0.005	0.044	0.013	0.018	0.027
	(0.043)	(0.045)	(0.045)	(0.043)	(0.041)	(0.045)
Days 85°F to 90°F	-0.036	-0.027	0.008	-0.036	-0.012	0.034
	(0.055)	(0.057)	(0.057)	(0.055)	(0.053)	(0.057)
Days > 90°F	0.016	0.036	0.062	0.016	0.031	0.089
	(0.058)	(0.064)	(0.061)	(0.058)	(0.056)	(0.064)
Sample size	2,234,842	2,234,842	2,234,842	2,234,842	2,148,231	2,148,231
Prior year weather	No	Yes	No	No	No	Yes
Prior year pollution	No	No	Yes	No	No	Yes
Economic conditions	No	No	No	Yes	No	Yes
Student SES	No	No	No	No	Yes	Yes

Notes: The dependent variable is the standardized NAPLAN test score multiplied by 100. "Prior year weather" includes measurements for rainfall, wind and humidity on school days in the past year and on the test day; "Prior year pollution" is based on the AQI index (see notes for Table 1); "Economic conditions" are measured using the average monthly regional unemployment rate over the 12 months prior to the NAPLAN test date; and "Student SES" is a measure of family socioeconomic status provided by the data custodian, derived from parental education and occupation. Other covariates not shown are, number of weekend days in previous 12 months with maximum temperatures in the same ranges as shown for school days in the table; max temperature on test day; age; gender; year-grade FE; school-grade FE. Standard errors clustered at school level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3 Estimated lagged and cumulative effects of temperature on NAPLAN test scores

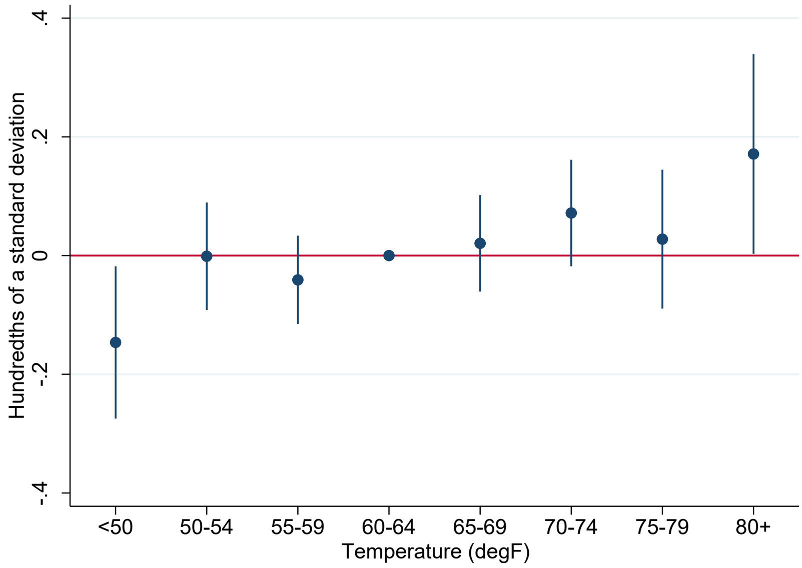
	(1)	(2)	(3)
Days below 70°F in previous year	-0.083***	-0.092***	-0.100***
	(0.021)	(0.022)	(0.026)
Days below 70°F 1 year earlier (t-1)		-0.079***	-0.084***
		(0.023)	(0.025)
Days below 70°F 2 years earlier (t-2)			-0.028
			(0.029)
Total effect (sum of presented coefficients)		-0.170***	-0.211***
		(0.036)	(0.062)
Number of observations	2,234,842	2,234,842	2,234,842

Note: Included covariates: Days below 70°F in the last 12 months; max temperature on test day; age; gender; year-grade FE; school-grade FE. Standard errors clustered at school level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix

Figure A.1 Estimates using Alternate Temperature Measures

A: Estimated test score effects of prior year school days with various mean temperatures



B: Estimated test score effects of prior year school days with various minimum temperatures

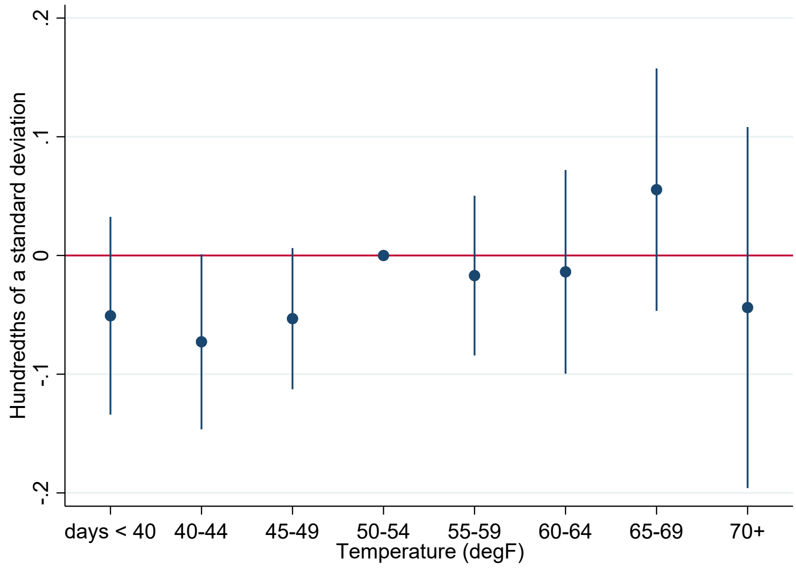


Figure A.2 Estimated Effects of School Day Temperatures in the Year After the Test

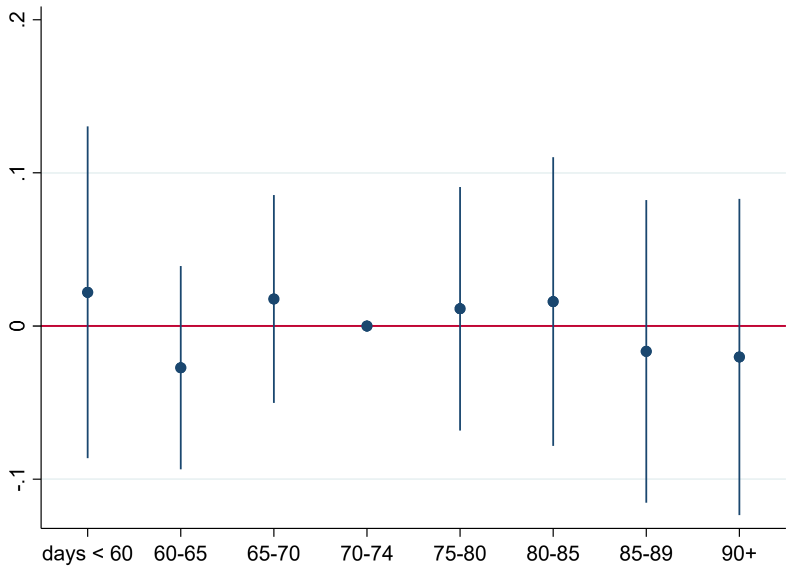


Table A.1 Detailed Regression Results for Model with Full Controls

	Coefficient	(S.E)
School days below 60°F	-0.116**	(0.058)
School days between 60°F and 64°F	-0.081**	(0.035)
School days between 65°F and 69°F	-0.055*	(0.032)
School days between 70°F and 74°F (omitted category)	-	-
School days between 75°F and 79°F	-0.002	(0.039)
School days between 80°F and 84°F	0.027	(0.045)
School days between 85°F and 89°F	0.034	(0.057)
School days above 90°F	0.089	(0.064)
Weekend days below 60°F	0.102	(0.116)
Weekend days between 60°F and 64°F	0.167*	(0.094)
Weekend days between 65°F and 69°F	0.197***	(0.075)
Weekend days between 70°F and 74°F (omitted category)	-	-
Weekend days between 75°F and 79°F	0.015	(0.066)
Weekend days between 80°F and 84°F	0.073	(0.072)
Weekend days between 85°F and 89°F	0.007	(0.101)
Weekend days above 90°F	-0.155	(0.125)
School days with no rain (omitted category)	-	-
School days with 0 – 0.5 mm of rain	0.027	(0.026)
School days with 0.5 – 4 mm of rain	-0.106***	(0.033)
School days with 4 – 16 mm of rain	-0.053	(0.040)
School days with 16 – 32 mm of rain	0.080	(0.056)
School days with 32 – 64 mm of rain	-0.005	(0.082)
School days with 64+ mm of rain	-0.001	(0.151)
Rain on test day (estimated)	0.267***	(0.102)
Age	-1.683***	(0.348)
Female	5.147***	(0.289)
Local Unemployment Rate	-0.158	(0.160)
Mean Pollution on School Days	-0.103*	(0.056)
Mean Wind on School Days	-0.036	(0.046)
Mean Relative Humidity	0.103	(0.085)
Student SEA quartile 1 (omitted category)	-	-
Student SEA quartile 2	22.957***	(0.413)
Student SEA quartile 3	41.526***	(0.545)
Student SEA quartile 4	70.218***	(0.800)
Test day maximum temperature	0.302*	(0.175)
_cons	-23.914**	(9.835)
N	2,148,231	

Notes: This table shows detailed results for the version of the model which contains full controls (as per Table 2 Column 6 Panel B). See also Table 1 notes.

Table A.2 Estimated Associations between Student Characteristics and Temperature

	SEA quartile (1)	Female (2)	Age (3)
School days below 60°F	-0.0008	0.0003	0.0002
	(0.0005)	(0.0003)	(0.0002)
School days between 60°F and 64°F	-0.0004	0.0001	-0.0000
	(0.0003)	(0.0002)	(0.0001)
School days between 65°F and 69°F	-0.0006**	-0.0000	-0.0001
	(0.0003)	(0.0002)	(0.0001)
School days between 75°F and 79°F	-0.0005	-0.0002	0.0002
	(0.0004)	(0.0002)	(0.0002)
School days between 80°F and 84°F	-0.0002	-0.0001	0.0003
	(0.0004)	(0.0002)	(0.0002)
School days between 85°F and 89°F	-0.0007	-0.0002	0.0004*
	(0.0005)	(0.0002)	(0.0002)
School days above 90°F	-0.0007	-0.0000	0.0003
	(0.0005)	(0.0002)	(0.0002)
r2	0.300	0.070	0.952
N	2149349	2236002	2236002

Notes: This table shows the results of tests of weather affecting selection into test taking. The dependent variable is quartile of student Socio-educational advantage (1=low, 4 = high) in column (1), female in (2) and age in years in (3). The specification otherwise follows the main analysis, as per Figure 3, excluding sex as an explanatory variable in (2), and age in (3). *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.